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EEG HYPERSCANNING TECHNIQUES FOR ASSESSMENT OF MUTUAL ENGAGEMENT

Faculty of Information Technology and Communication Sciences
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ABSTRACT

Ahmad Sharif: EEG HYPERSCANNING TECHNIQUES FOR ASSESSMENT OF MUTUAL ENGAGEMENT
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Hyperscanning is the study of multiple brain activities simultaneously while partic- ipants engage in a common task. In recent times, hyperscanning has gained much attention in the research area to investigate social interaction, mutual engagement tasks, teamwork, and so on.

Electroencephalography, or EEG, is a non-invasive neuroimaging technique to mea- sure the brain's electrical activity. It measures the brain's neural activity when electrodes are placed on a scalp. EEG devices are ideal for hyperscanning due to their excellent temporal resolution, portability, wireless capability, and low cost. In this EEG hyperscanning recording setup, the leading equipment included two Bluetooth-enabled computers, EEG devices such as the Muse S and Unicorn Hybrid Black, a local area network (LAN), and corresponding applications like LabRecorder and MuseLSL2/Unicorn Suite. The popular Tetris game was chosen to assess the mutual engagement of two par- ticipants while they were relaxing and also played three different versions of the Tetris game. The recordings had four Relaxation phases, and three Tetris games were played. Later, these phases were classified, such as Relaxation vs Game as bi- nary and Game1 vs Game2 vs Game3 as multi-class classification. It was observed that binary classification, such as Relaxation vs. Game, outperformed multi-class classification in performance. Interestingly, for binary classification, the Unicorn cross-coherence features provide consistent results across both random and Leave- One-Subject-Out (LOSO) Cross-Validation in all metrics. The total sample size was 10, which is relatively small. More sample data is required to draw any conclusive statement.

Keywords: EEG, Hyperscanning, Neuroscience, Mutual Engagement

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Contents

List of Abbreviations

Abbreviations

ACC	Accelerometer
AD	Alzheimer's Disease
CNN	Convolutional Neural Networks
CT	Computed Tomography
CV	Cross Validation
EEG	Electroencephalogram
fNIRS	Functional Near-infrared Spectroscopy
fMRI	Functional Magnetic Resonance Spectroscopy
LOSO	Leave-One-Subject-Out
MRI	Magnetic Resonance Imaging
MSC	Magnitude-squared coherence
PSD	Power Spectral Density
PET	Positron Emission Tomography
PPG	Photoplethysmography
UI	User Interface
XDF	Extensible Data Format

CHAPTER 1

Introduction

Researchers are always interested in analyzing the human brain because it controls human actions. The human brain contains billions of interconnected, and they are responsible for human behaviours in different circumstances. For this reason, scientists are always keen to research the human brain to answer many questions. However, It is a comparatively challenging job to experiment with the human brain because it is the most complicated and sensitive organ of the human body. Several scientists have attempted to read brain functionality for over a century.

Due to technological advancement, many tools and techniques have been invented to study human brains in recent times. These tools and techniques are widely used clinically to detect human brain-related diseases like epilepsy, Alzheimer's, mental stress, and dementia [1].

On the other hand, researchers investigate brain data to find interesting patterns and answer different questions. Many advanced EEG devices have been commercially available in recent times to read brain signals.

Magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG), and Electroencephalography (EEG) are some techniques that are used to read brain activities. Among the techniques, EEG reads electrical activity in the brain to measure cognitive processes of the brain. EEG is relatively low-cost, noninvasive, painless, safe, and portable. EEG devices have electrodes that are placed on the scalp of different parts of the head to record the brain's electrical activities [2].

Researchers investigated the single human brain, and they used different neuroimaging techniques for a while. However, traditional single-brain analysis can't examine social interactions like one-on-one or one-to-many. Additionally, The neural processes responsible for these interactions have remained largely unexplored [3]. That's why scientists and researchers are interested in studying different interesting patterns.

HyperScanning refers to a neuroimaging technique in which multiple brain activities are recorded at the same time during real-time social interactions. It was first introduced in 2002 by Montague to study social exchanges [3]. HyperScanning has been used to investigate inter-brain synchrony and coherence against time [4].

In our social life, human beings interact with each other for different purposes. It ranges from non-verbal communication between the child and mother to complex group activities. Creative and performing arts are the most complicated group activities, such as band music, where musicians synchronize their instruments with vocalists to maintain rhythm, harmony, and sound. In such cases, verbal and non-verbal communication among the members is required. Moreover, in group dance, performers rely on precise timing, gestures, and eye contact to align with fellow dancers.

This thesis aims to set up EEG hyperscanning using low-end mobile devices and record brain signals via EEG devices with relevant applications.

The research questions of the thesis are:

1. What is a feasible setup for EEG hyperscanning using low-end wireless devices, and what problems will be faced?

2. Can inter-person EEG synchronization be detected from hyperscanning recordings with low-end wireless devices using EEG spectral features and a neural network classifier?

CHAPTER 2

EEG Hyperscanning Techniques and Setups

This chapter provides an overview of EEG signals and their applications, followed by an exploration of the emerging field of EEG hyperscanning. First, the origin and history of EEG are discussed, tracing the development of this technology from its discovery to its current role in neuroscience and clinical applications. Next, the methods of EEG measurement, their properties, the classification of EEG rhythms, and the various applications of EEG are examined.

The second part of the chapter focuses on EEG hyperscanning. This section covers the properties and applications of hyperscanning, highlighting its ability to uncover inter-brain synchrony. Additionally, it discusses the challenges associated with setting up hyperscanning experiments.

2.1 Origin and History of EEG

A mature human brain contains hundreds of billions of neurons [5]. A neuron, shown in Figure 2.1, is the fundamental unit of the brain. Neurons are specialised cells responsible for processing, sending, and receiving information. A neuron has three main components: dendrites, axons, and cell bodies (or soma). The soma, the central part of the neuron, has extensions at one end called dendrites, which are responsible for receiving information from the environment or other cells.

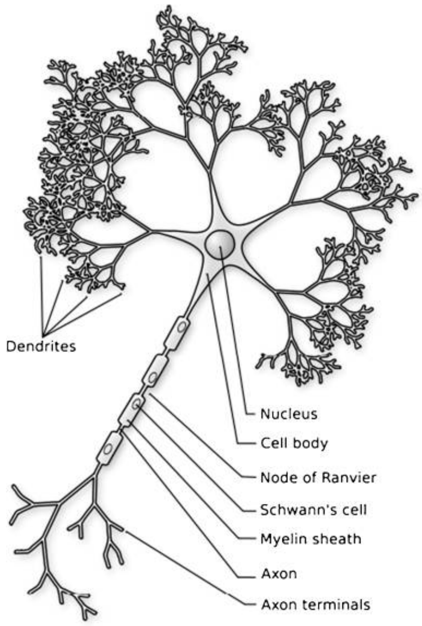


Figure 2.1 *Main structure of a neuron Source:* *https://pmc.ncbi.nlm.nih.gov/articles/PMC2989000/*

Neurons communicate with each other by using both electrical and chemical signals. Communication between neurons occurs through electrical impulses, action potentials, and chemical signals at synapses. When a group of neurons, particularly pyramidal neurons, activate simultaneously, their microscopic electrical currents generate a larger regional current. This combined electrical current contributes to the generation of voltage in the brain.

EEG signals recorded from the scalp result from these combined microscopic electrical currents generated by many active neurons. When groups of pyramidal neurons activate simultaneously, they produce a larger current, creating a measurable voltage. This voltage can be detected on the scalp by using EEG devices [6] [7] [8].

The history of EEG dates back several centuries. In 1875, a British physician, Richard Caton first observed electrical signals in animals' (Rabbits and monkeys) brains through the galvanometer. The electrical oscillation that came from the brain was biological, and he verified it by using chloroform[9]. Additionally, Vladimir Vladimirovich Pravdich-Neminsky, a Russian Physiologist, also found electrical signals in a dog's brain [10].

German neurologist and psychiatrist Hans Berger recorded the first brain signals from a human in 1924 [10]. 1935 American neurologist Frederic Andrews Gibbs first documented 3 Hertz spike-and-wave discharges during clinical seizures [11]. Many other notable scientists, like Davis and Lennox, worked with Gibbs simultaneously. The first EEG laboratories for clinical purposes were founded in the United States

in the 1940s, and in 1947, the American EEG Society—now the American Clinical Neurophysiology Society—was officially formed [12].
At this time, EEG monitoring systems had been developed, and EEG had been used clinically for conditions such as epilepsy and sleep disorders.

2.2 Measurement and Properties of the EEG

EEG signals are extracted from the scalp by using electrodes. Electrodes are located according to 10-20 electrode placement system [13]. The International 10-20 placement system refers to how electrodes are placed on different parts of the scalp. The 10-20 electrode placement system was introduced by Herbert Jasper at the Brussels IV International EEG Congress in 1957 to unify EEG electrode placement practices [14].
In the 10-20 system, the measurement is taken over the top of the head, starting from the nasion (bride of the nose) to the inion(the back bump of the skull). The terms "10" and "20" specify that the distance between electrodes equals 10 or 20 per cent of the skull's full front-back or side-to-side measurement. Figure 2.2 (a) illustrates different electrode location.
The following locations are marked in the vertex line from nasion to inion by letters: Fp (pre-frontal or frontal pole) F (frontal), C (central line of the brain), T (temporal), P (parietal), and O (occipital).
The first point, "Fp," is 10% of the nasion-inion distance. The second point, "F," is 20% of the distance from "Fp," and this pattern continues in 20% steps. Lastly, the distance from "O" to the inion is 10%.
Electrode names follow anatomical terms for the brain lobes, except the central region since there is no central lobe. Even numbers are used for the right hemisphere and odd numbers for the left. The letter "z" denotes an electrode located on the midline. Figure 2.2 (b) figure illustrates difference brain lobes position.

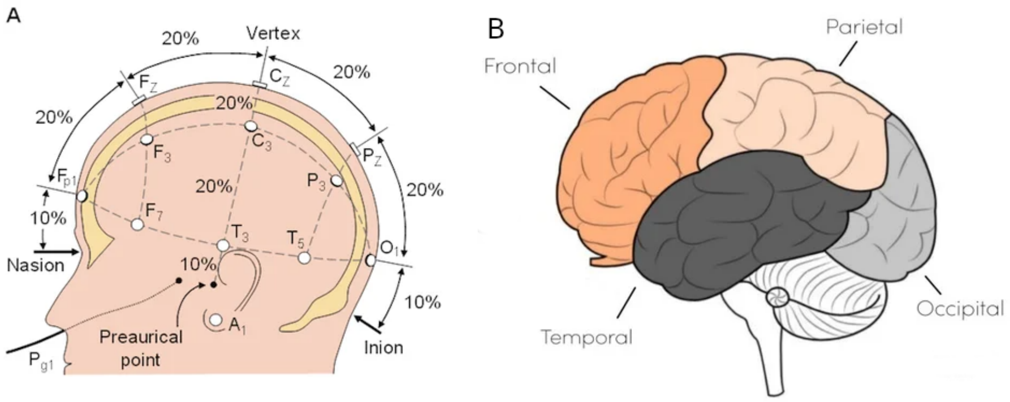


Figure 2.2 (a) 10–20 EEG electrode location system. (b) Location of the frontal, temporal, parietal, and occipital lobes of the human brain.
Sources: [15], [16]

EEG Properties

EEG has several vital properties. They are non-invasive, painless, safe, and cost-efficient, making them popular for monitoring brain activity. EEG's high temporal resolution, which allows for millisecond-level recording of brain activity, is valuable for detecting rapid changes in neural processes. However, it has limited spatial resolution, meaning it cannot provide exact locations of brain activity with high precision. EEG is typically non-stationary, meaning that their statistical properties (such as mean and variance) can change over time [17]. The most common sampling rate of EEG devices can range from 128 to 1024 Hz [18].

Classification

The EEG signal is usually divided into five rhythms, each related to a specific frequency band, and these rhythms are identified using Greek letters.. The waveforms are divided into five groups, each associated with specific neural activities. The frequency bands and their associated rhythms can be found in Table 2.1

Delta: Its frequency ranges from 0.5 to 4 Hz. It is the slowest wave. It appears during deep sleep, coma and anaesthesia.

Theta: Theta frequency ranges from 4 to 8 Hz. It usually suggests slow activity. This frequency is noticed during relaxation and meditation [19].

Alpha: Alpha frequency ranges from 8 to 13 Hz. It usually suggests a relaxing mode. It is observed while we close our eyes.

Beta: Beta frequency ranges from 14 to 30 Hz. It usually suggests alertness and activity, and this frequency band is observed during significant attention tasks.

Gamma: Gamma frequency ranges over 30 Hz. It is linked to deep cognitive tasks. It is linked with perception and consciousness [20].

EEG rhythm	**Frequency range, Hz**	**Brain state**
Delta (δ)	0.5 – 4	Deep sleep
Theta (θ)	4 – 8	Relaxation and meditation
Alpha (α)	8 – 13	Eye closed
Beta (β)	14 – 30	Concentration
Gamma (γ)	> 30	Cognitive activities

Table 2.1 *EEG rhythms and corresponding brain states*

Common Applications of the EEG

Many EEG devices, tools, and techniques have been developed in the last decades. Thus, the use of EEG has been expanding over time. Electroencephalography (EEG) plays a vital role in diagnosing neurological disorders. EEG is used for diagnosing different neurological disorders such as epilepsy, brain injuries and other variety of brain dysfunction. The presence of disorders such as autism, Alzheimer's, epilepsy, Parkinson's, brain tumours, and stroke can be verified or disproved through EEG analysis. EEG is applied in the behavioural sciences, covering areas from basic cognition to emotional functions [21]. Thus, it has great value in research fields. Researchers use EEG data and analysis to find interesting patterns that uncover many questions in neuroscience, psychology, physiology, sports, lifestyle, etc. Despite these advancements, much remains to be explored and discovered. In the following section, a brief discussion of the common applications of EEG will be provided.

Epilepsy: Epilepsy affects fifty million people worldwide, the majority of whom 85% are in developing countries. Epilepsy is a condition where repeated seizures occur. It is also called a disorder of seizures. Our brain consists of billions of cells that are called neurons. It generates electricity while neurons communicate with each other by swapping chemicals. In some cases, additional electricity is generated, thus creating an unusual movement or sensation in a person, which is referred to as epilepsy. Repeated seizures that occur suddenly can be harmful and potentially life-threatening [22].

Sleep Disorder: The absence of sleep can result in diseases such as obesity, heart-related diseases, and diabetes, and life expectancy can be decreased as a consequence. Sleep stages can be classified through EEG, utilizing time-frequency images to evaluate sleep quality [23].

Anesthesia: Anaesthesia refers to keeping out of physical pain, which is extensively used in surgery. It is a state of unconsciousness, amnesia, hemodynamic, motor, and endocrinologic stability [24]. EEG is used to measure the level of consciousness and anaesthetic state. Anesthesiologists examine EEG patterns, such as burst suppression, to assess the depth of unconsciousness.

Coma: Coma refers to a pathological state of deep unconsciousness where a person cannot respond to external or internal signals [25]. It can sometimes last from hours to weeks or months. EEG can provide information about the coma state and follow its development to obtain a prognosis. After cardiac arrest, several patients might experience a coma state due to brain damage. It also evaluates comatose patients in the intensive care unit (ICU).

Dementia: Dementia refers to a lack of cognitive abilities to remember events. It refers to various disorders caused by the gradual deterioration and death of brain cells. Generally, ageing people experience dementia. However, in many cases, younger people also suffer from this brain disorder [26]. To detect the early stage of dementia in younger people, many biomarkers already exist, such as computerised tomography scans (CT) and magnetic resonance imaging (MRI). The following tools are expensive and require specialised lab rooms and technicians.

EEG is regarded as a potential biomarker due to its affordability, high temporal resolution and accessibility.. EEG can evaluate physiological and pathological conditions like the changes in cortical function caused by dementia. It is effective for clinical diagnosis and anticipating dementia progression [27].

Alzheimer: Alzheimer's disease (AD) is related to dementia disease because it is the most common cause of dementia [28]. Abnormal protein deposits, or plaques and tangles, form in the brain during Alzheimer's disease. These deposits damage nerve cells, causing the brain to shrink. Several brain imaging methods, including PET (Positron emission tomography), MRI, and CT (Computerised tomography) scans, are used to identify abnormalities and act as early screening tools for disease detection [29] [30] [31].

2.3 Recording EEG in Real-Life Settings

Several factors contribute to obtaining reliable EEG data in a real-life EEG recording setup. First and foremost, a suitable EEG device is required. An EEG device with good signal quality is portable, easy to use, and consumes less power.

EEG devices come in two main types: clinical and consumer-grade. Clinical devices are used in controlled settings with more electrodes for precise recordings, while consumer-grade devices usually have fewer electrodes. Muse, Unicorn Hybrid Black, OpenBCI, and Emotiv Insight are widely used EEG devices.
The following equipment is needed for EEG recordings: an EEG device, Bluetooth computer. A corresponding program must also be required to read and process EEG data.
Apart from the EEG device, the environment in which the recording occurs is equally essential. A comfortable indoor setting with a consistent power supply helps to avoid disruptions during the recording process. Furthermore, the participant should be healthy and free from brain-related diseases or injuries. It is also recommended that the participant have short or trimmed hair, as this allows for smoother extraction of brain signals, ensuring minimal interference during data collection.

2.4 EEG Hyperscanning

Humans are inherently social as we depend on each other to reach goals we cannot accomplish alone [32]. However, the brain mechanisms behind these interactions are still mostly unknown. Recent studies on brain activity during social interactions have typically focused on one person, often in unrealistic social situations [3]. Social interaction analysis requires data from multiple people, allowing us to analyse correlation and contradiction, which are absent in single-brain analysis. These social interactions can be analysed with hyperscanning.
EEG hyperscanning is recording EEG data from multiple subjects simultaneously, usually while they are engaged in the same task [33]. It can extract social interaction data. Often, the term ”interbrain synchrony” is also used interchangeably. Additionally, many studies suggest that hyperscanning is valuable for studying cooperative behaviour [34], [3].
For hyperscanning, EEG is a better option because it is non-invasive, low-cost, and does not require a specialised room. Research suggests EEG-based hyperscanning performs better temporal resolution during social cognitive tasks [35].
For EEG hyperscanning recording setup, the LabRecorder application makes things simple because it comes up with LSL, a data streaming protocol. LabRecorder is used to record and synchronise multiple streams into one single file [36].
In 1965, Duane and Behrendt conducted the first EEG study on brain activities between people, recording the brainwaves of identical twins simultaneously and comparing them [37]. 2002, the first hyperscanning study was published, studying the

neural dynamics of social interactions [3].
As shown in Figure 2.3, brain data from two subjects are recorded simultaneously.

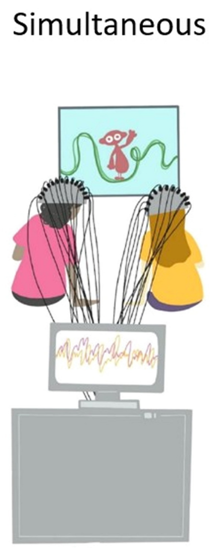


Figure 2.3 *Extracting brain signals simultaneously Source:* *https://www.sciencedirect.com/science/article/pii/S1053811923005050*

2.4.1 Hyperscanning Extends Beyond Single-Brain Studies

Research on brain functions has primarily focused on individual brain activity for over a century. While humans have long been recognised for their inherently social nature, it is only in the last decade that scientists have begun to explore brain activity during social interactions [38]. However, data on social interactions remain limited or unrealistic when derived from studies focused on a single brain [3].
Social interaction starts from the very first day a child is born. A child begins to communicate with her mother on a small scale using non-verbal signals such as smiling, crying, touching, body scent, and physical movements. We human beings gradually build and develop social skills according to social contexts [39]. The inter-brain synchronization involved in social interactions can be understood through hyperscanning [40]. Additionally, social neuroscience explores the neural mechanisms behind social cognition, which involves cognitive skills like empathy, emotion recognition, cooperation, and altruism [41].
Nowadays, hyperscanning is an effective method to explore social interactions and joint actions [42]. It has been used in studies of movement imitation [43], musical instrument performance [44], and spoken communication [45].
However, the process of extracting social interactive data is not so easy to perform for several reasons. It has been observed that people act differently in different social

circumstances [46], and it does not provide natural behaviour data when subjects are trained for particular social activities [47].

Our social interactions contain emotions, happiness, sadness, fear, anger, surprise, love, and many other states of mind. Research suggests that our mental peace is also correlated with social interactions [48]. New research in the field of social neuroscience suggests that studying the brain's activity during interactions can provide insights into people's mental processes [49].

That's why it is important to study different social interactions to find interesting patterns in other social circumstances.

2.4.2 Exploring Joint Tasks with EEG Hyperscanning

Different types of joint tasks have been conducted in our daily lives. Two or multiple individuals perform these joint tasks, which are different in nature. Briefly, cooperation and competition are the two most common and opposite forms of social interactions [50].

Cooperative refers to multiple people performing one task or job by splitting or dividing the task. Cooperation is essential because cooperation among individuals can solve complex and creative problems [51]. This attribute makes us different from other species and is represented by the development of the relatively larger neocortex in the human brain [52].

Various brain couplings have been uncovered among friends, strangers, colleagues, musicians, lovers [53], teacher-student pairs, and mother-child interactions during activities like cooperative singing [54], gaming [55], and video watching [56]. Cooperation and competition [57] are central to human interactions, with more robust inter-brain synchrony during cooperation compared to competition [55].

2.4.3 Applications of EEG Hyperscanning

EEG hyperscanning has excellent potential in areas ranging from clinical to daily lifestyle matters. It can be used to assess group performance and detect coordination among team members. The following are some areas that can use hyperscanning.

By measuring Interbrain Synchrony (IBS), researchers have uncovered how neural alignment contributes to effective team dynamics. This aligns with the Input-Process-Output (IPO) model, where IBS serves as a critical metric for assessing collective processes like communication and decision-making. EEG hyper scanning has been applied to various scenarios:

- **Teamwork Studies:** Usually, a team refers to two or multiple independent individuals who help each other to perform a task [58]. Hyperscanning can be used to measure teamwork performance because collaboration is one of the main action processes of teamwork [59], and it is often referred to as cooperation or collaboration [60].

- **Emotional Synchrony:** EEG hyperscanning captures real-time alignment of emotional states, helping to study how shared emotions influence group behaviour. Research suggests movement synchrony in groups is correlated to the presence of positive emotions [61].

- **Conflict and Resolution:** In a team, while they are involved in a common task, they process and represent different states of mind such as affective, behavioural, and cognitive [62]. Thus, EEG hyperscanning can be used to detect desynchronisation among the team members [63].

2.4.4 Challanges of EEG Hyperscanning

Choosing the right EEG device is challenging. In current market, many consumer grade EEG device is available. However, it is challenging to choose the right EEG device for research purposes.
Brain activity seen in hyperscanning might not actually show real brain-to-brain interaction during social interactions. This means the brain activity could be due to the shared stimulus, not necessarily because the participants are genuinely interacting with each other's brains. So, it's essential to separate brain activity caused by external factors from genuine communication between brains [64]. Additionally, EEG data are inherently noisy, which makes learning models likely to overfit.

CHAPTER 3

Analysis methods

3.1 Introduction to Analysis Methods

EEG hyperscanning refers to the simultaneous recording of two or more individuals' brain activity while participants interact. This technique is used to study social interaction and cognitive and emotional processes, allowing researchers to explore inter-brain connectivity and synchronization. In this chapter, different analysis methods and their challenges will be discussed briefly.

3.2 Preprocessing Techniques

Preprocessing is crucial in EEG hyperscanning to clean the raw data and prepare it for analysis. The goal is to remove noise, artifacts, and irrelevant signals while preserving neural activity.

Artifact and Noise

EEG artifacts are present in EEG data and can have a significant impact on the recordings. EEG signals are commonly contaminated by electrical properties [65]. These artifacts can be classified into physiological (from within the body) and non-physiological (external). Physiological signals, such as eye blinks, muscle activity, and heartbeats, are considered physiological artifacts. Some artifacts come from environmental noise and are called environmental artifacts. A filter can eliminate these, as their frequency differs from the desired signals.

A band-pass filter removes low-frequency drifts and high-frequency noise (such as EMG or electrical interference), making the signal cleaner and more understandable [66]. The raw EEG data is further processed using techniques like resampling and segmentation. The raw EEG data is then prepared for further processing through resampling and segmentation.

3.2.1 Feature Extraction

Feature extraction involves converting the cleaned EEG signals into meaningful features that can be used for further analysis, including classification or modeling. The purpose of feature extraction is to reduce the complexity of the raw data while maintaining its essential information, making it easier to analyze with machine learning (ML) models, particularly in medical applications. EEG signals are (a) non-stationary, (b) non-linear, (c) non-Gaussian, and (d) non-short form. These characteristics mean feature extraction must be carefully designed to handle these complexities [67]. Overall, feature extraction saves on hardware and software resources computational time and reduces complexity,

Time-Domain Features: Time-domain features are derived directly from the raw EEG signal. These include measures such as amplitude, which reflects the strength of neural activity, and peak-to-peak analysis, which measures the difference between the highest and lowest points of the signal in a given window. These features can provide insights into the overall dynamics of brain activity during different tasks or conditions.

Power Spectral Density (PSD): PSD is a key frequency-domain feature in EEG analysis. It measures power distribution across various frequency bands, helping identify rhythmic brain activity linked to different cognitive or emotional states. By analyzing PSD, we can observe how the brain's electrical activity varies over time and under various conditions.

3.3 Inter-Brain Synchronization (IBS) Measures

Inter-brain synchronization refers to the alignment of neural activity between individuals during social interactions, where their brain waves become temporally synchronized. This phenomenon is believed to play a crucial role in enhancing social bonding, cooperation, and prosocial behaviors. Studies have shown that synchronized actions between people, such as those involved in rituals, can lead to stronger group cohesion [68]. In these interactions, not only are physical actions synchronized, but neural activity also aligns, particularly in regions of the brain related to communication and empathy [69].

The concept of inter-brain synchronization has been explored through various neuroimaging techniques like EEG, fMRI. These studies have revealed that when individuals interact in person, their brain activity tends to synchronize, with higher synchronization linked to positive social outcomes, such as better cooperation, rapport, and agreement [70].

However, this synchronization is not solely based on physical co-presence. Studies suggest that even when individuals are in separate rooms or interact through digital media, inter-brain synchronization can still occur, though its strength and nature may differ. Understanding the mechanisms behind inter-brain synchronization is essential for exploring its role in both physical and virtual social interactions [71].

Coherence: Coherence is a frequency-specific measure that quantifies the degree of correlation between signals at each frequency. It reflects the strength of the linear relationship between signals in the frequency domain, providing insights into the synchrony of brain oscillations across participants. High coherence at specific frequencies indicates a strong shared neural rhythm, which may be related to cognitive or emotional processes.

The magnitude-squared coherence is used to assess the relationship between two EEG signals, helping us understand how synchronized the brain regions are at various frequencies. This is particularly useful when analyzing brain interactions during tasks or comparing neural activity across multiple subjects.

3.4 Machine Learning Techniques

Machine learning is a subset of artificial intelligence that helps machines to learn from data. Statistical learning methods, which are the key to creating machine intelligence [72].

Supervised Learning: In supervised learning, the model is trained using labeled data, where the input features are associated with known outcomes. This approach relies on prior knowledge of the outcomes, enabling the model to learn patterns and relationships within the data to make accurate predictions.

Unsupervised Learning: This method is used when labeled data is unavailable. It focuses on finding hidden patterns or groupings in the data, such as clustering brain activity states or identifying common features across subjects. Unsupervised learning methods aim to discover underlying structures in the data without the need for pre-labeled outcomes, which is useful in exploratory analysis and data mining.

3.4.1 Deep Learning Techniques

Deep learning evolved from artificial neural networks and has now become a popular area of machine learning. Deep learning involves automatically learning various layers of data representations to understand the data's underlying distribution [73]. In simpler terms, deep learning algorithms automatically extract the essential features for classification, both basic and advanced. High-level features are those that are built upon other features in a hierarchical structure.

3.4.2 Convolutional Neural Networks

A typical layer in a convolutional neural network (CNN) has three stages. First, it performs multiple convolutions in parallel to generate linear activations. Second, these activations are passed through a nonlinear activation function, such as ReLU, to introduce non-linearity and help detect complex patterns. This stage is called the "detector" stage. Lastly, a pooling function (e.g., max pooling) is applied to reduce the output's spatial dimensions by summarizing nearby activations. Pooling helps make the network more efficient and less sensitive to small changes in the input, focusing on the most important features [74] [75]. Figure 3.1 illustrates a CNN architecture.

A convolutional neural network usually have following components:

Convolutional Layer: The convolutional layer applies small filters (or kernels) to the input data (such as an image) to detect specific features like edges or textures. These filters slide over the input, producing feature maps that highlight important patterns at different locations in the input. The convolution operation is crucial for recognizing spatial hierarchies in the data.

Activation Function (ReLU): After convolution, a nonlinear activation function like the Rectified Linear Unit (ReLU) is applied to the feature maps. ReLU introduces non-linearity, allowing the model to learn more complex patterns and preventing issues like vanishing gradients, which can hinder training in deep networks.

Pooling Layer: Pooling layers are used to downsample feature maps by summarizing the most important information. This helps reduce the computational load and the number of parameters, making the network more efficient. Max pooling and average pooling are common methods, where max pooling selects the maximum value in a feature map region, and average pooling calculates the average value.

Fully Connected Layer: The fully connected (FC) layer is responsible for making the final predictions. After several convolution and pooling layers, the feature maps are flattened and passed through fully connected layers. These layers combine the learned features and produce a classification or regression output. The last fully connected layer typically outputs the predicted class probabilities for classification tasks, using activation functions such as softmax or sigmoid [74].

Output Layer: The output layer presents the final predictions. For classification tasks, this layer uses softmax (for multi-class) or sigmoid (for binary classification) to output the probability of each possible class, helping the model make decisions.

Training: CNNs are trained using a process called backpropagation, where the weights of the network are adjusted based on the error (loss) between predicted and true values. Optimization algorithms like Gradient Descent or Adam are used to minimize this error, improving the model's accuracy over time.

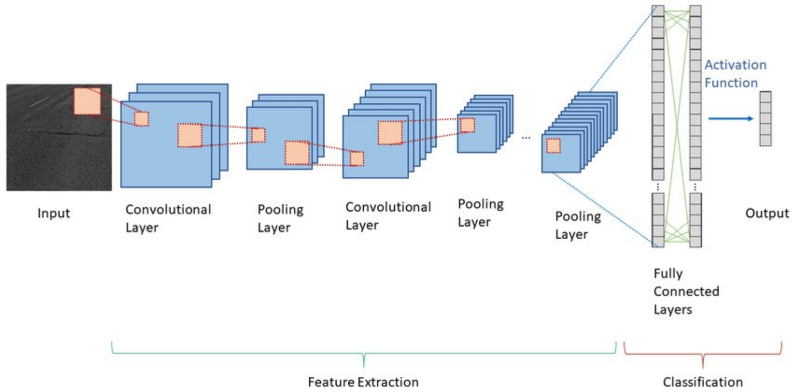


Figure 3.1 *A CNN architecture Source:* `https://www.linkedin.com/pulse/decoding-cnn-architecture-unveiling-power-precision-neural-moustafa/`

Optimization in Neural Networks

Neural network optimization focuses on improving the performance of deep learning models using activation functions, loss functions, and optimization algorithms. Advanced methods like Adam improve the optimization process by adapting the learning rate, ensuring faster convergence and better performance, especially in complex tasks.

Different Optimizers: Optimizers like Adam, Adagrad, and SGD are fundamental in neural network training. Adam, for example, adam is an optimization algorithm that helps the model learn better by adjusting the learning rate over time. It combines two methods: momentum (which helps the model keep moving in the right direction) and RMSProp (which scales the learning rate based on past gradients). Adam uses both of these techniques to improve learning and make the process more efficient. The decision on which algorithm to use mainly depends on how familiar the user is with the algorithm, as this makes hyperparameter tuning easier [75].

Batch Normalization: Batch normalization is a technique that normalizes the input to each layer by adjusting and scaling the activations. This helps to maintain the distribution of activations across different layers and allows the model to converge faster. It also helps mitigate the problem of internal covariate shift, where the distribution of inputs to a layer changes during training [75].

Dropout: Dropout is a regularization method where random units (neurons) are dropped out during each training step. This prevents overfitting by forcing the network to learn redundant representations. Dropout is especially useful in large neural networks where overfitting is common, particularly when the training data is limited.

Learning Rate Scheduling:

Neural network researchers have long recognized that the learning rate is one of the most difficult hyperparameters to set, as it significantly impacts model performance. If the learning rate is too large at the start, it can cause overshooting, while if it's too small, convergence becomes slow. To address this, learning rate scheduling is used, which dynamically adjusts the learning rate during training—either by reducing it over time or based on performance metrics—ensuring more efficient and stable convergence [75].

3.4.3 Manual Hyperparameter Tuning

Manual hyperparameter tuning is the process of selecting and adjusting a model's hyperparameters based on experimentation and domain knowledge, rather than using automated optimization techniques. It is a straightforward method that can be useful when computational resources are limited or when the hyperparameters are well understood. In this process, key parameters like learning rate, batch size, and the number of layers in a neural network are adjusted iteratively to improve model performance. By testing different combinations of these parameters and evaluating the model's performance after each change, researchers can fine-tune the model to find the best configuration, aiming to minimize generalization error while considering resource constraints such as memory and runtime [75].

3.4.4 Cross-Validation

Splitting a dataset into a fixed training and test set can cause problems, especially if the test set is small. A small test set can lead to uncertainty, making it difficult to compare models like algorithm A and algorithm B. Cross-validation solves this issue by dividing the dataset into several parts. The model is trained and tested on different combinations of these parts, giving a more accurate estimate of its performance. This method is especially helpful for small datasets like EEG data, as it helps avoid overfitting and ensures the model performs well on new data [75].

- **Random Cross-Validation:** In Random cross-validation, the dataset is randomly divided into training and testing subsets multiple times. This technique provides a more flexible and potentially more accurate estimate of model performance, as it minimizes bias related to data splitting and ensures that the model is evaluated on a variety of different data combinations.

- **Leave-One-Subject-Out (LOSO) Cross-Validation:** Leave-One-Subject-Out (LOSO) cross-validation method is commonly used. This technique involves using data from all subjects except one for training, and then testing the model on the data from the excluded subject. This helps assess the generalization of the model across different participants. It is widely used in clinical predictions.

3.4.5 Performance Metrics

In machine learning, evaluating performance helps determine how well classification models are performing. These metrics help assess the model's ability to differentiate category. Classification tasks can be divided into binary (two categories) and multi-class (more than two categories). Different metrics are used to evaluate the performance of a classification model.

Confusion Matrix

A confusion matrix displays a summary of predictions in a matrix format. It shows how many predictions are correct or incorrect for each class and helps identify which classes the model mistakes for others [76].

Sensitivity

Sensitivity refers correct positive result divided by all positive results.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Specificity

Specificity is the correct negative test result, divided by all negative results.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Accuracy

Accuracy is the proportion of all classifications that were correct, whether positive or negative. It is mathematically defined as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

where,

- **True Positives (TP):** The total instances correctly classified as the positive class.
- **False Positives (FP):** The total instances incorrectly classified as the positive class.
- **True Negatives (TN):** The total instances correctly classified as the negative class.
- **False Negatives (FN):** The total instances incorrectly classified as the negative class.

CHAPTER 4

EEG Hyperscanning for the Detection of Mutual Engagement

This chapter will discuss the details of the EEG hyperscanning setup, EEG devices, and practical challenges. Choosing mental workload tasks and recording the brain's electrical activity simultaneously are essential for hyperscanning. The objective is to study the hyperscanning data of two participants to find interesting patterns.

4.1 EEG Devices

EEG data acquisition from multiple brains requires EEG devices. Several EEG devices are commercially available in the market. Muse S, Unicorn Hybrid Black, and Brain Bit are popular EEG devices. This study used the following EEG devices, as shown in Table 4.2. In this section, both EEG devices will be discussed briefly.

Table 4.1 *EEG Devices*

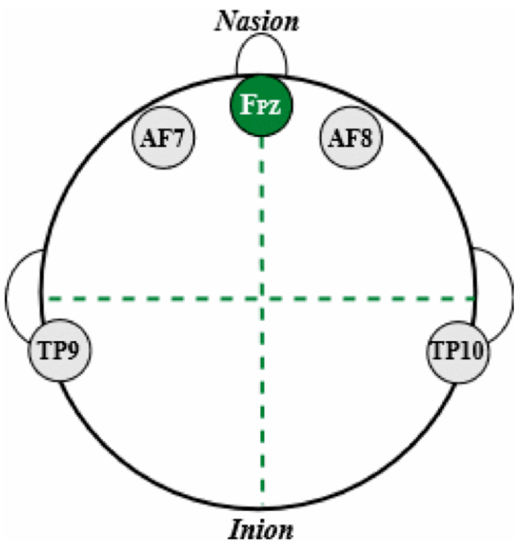
Company	Device Name	Channels	Sampling Rate
InteraXon	Muse S	4	256 Hz
g.Tec	Unicorn Hybrid Black	8	250 Hz

Table 4.2 *EEG devices*

Muse S

The Muse S is a flexible, compact, economical, and easy-to-use headband manufactured by InteraXon, a Canadian company. Designed primarily for reading EEG signals, it can also record photoplethysmography (PPG), accelerometer, and gyroscope data. Figure 4.1 (a) displays the Muse S headband.
This study employed four EEG channels of the Muse S headband—AF7, AF8, TP9, and TP10—to record participants' EEG signals. However, only the AF7 and AF8 channels were used, as they provide better signal quality. Prefrontal channels located on the forehead in a hairless area are preferred for EEG recordings due to their improved signal quality. The electrode locations of the Muse S headband are shown in Figure 4.1 (b), with the reference electrode.

(a) Muse S headband



(b) Muse S channels location

Figure 4.1 *Muse S and its electrode location Source:* `https://choosemuse.com/products/muse-s-gen-2` *and* `https://ieeexplore.ieee.org/document/10004658`

Unicorn Hybrid Black

The Unicorn Hybrid Black, developed by g.tech, is an affordable wireless EEG headset with eight electrodes, including FZ, C3, CZ, C4, PZ, PO7, OZ, and PO8. It samples at 24-bit resolution and 250 Hz per channel. It is mainly for EEG signals but can also measure gyroscope and accelerometer data. The Unicorn Hybrid Black package usually contains a software suite, Unicorn EEG gel, sticky electrodes, a syringe, a Bluetooth dongle, an EEG cap, a rechargeable battery, and other components. It runs with a rechargeable battery and lasts approximately three hours after full recharge. Unicorn software suite is used to check signal quality and record EEG data [77]. The Unicorn Hybrid Black headset is displayed in Figure 4.2.

Figure *4.2 Unicorn Hybrid Black Source:* *https://www.gtec.at/product/unicorn-hybrid-black*

4.2 Recording setup

Hyperscanning refers to extracting multiple brain neural recordings at the same time. In this study, EEG hyperscanning and two participants' brain signals were recorded simultaneously. The following equipments and peripheral devices are required for the setup of the recording for EEG hyperscanning.

1. EEG supported device: Muse S and Unicorn Hybrid Black;
2. two Computers/Laptops/Raspberry Pi that support Bluetooth technologies;
3. Ethernet Switch and cables;
4. common keyboard that two participants can operate;
5. common monitor for displaying the same game;
6. applications: MuseLSL2, Unicorn Suite, LabRecorder, Keyboard Stroke program (Python Script).

Figure 4.3 illustrates the EEG hyperscanning setup with all equipment and devices in place. The EEG computer connects to the same network via an Ethernet switch and cables. Two participants, who are healthy and have no brain-related issues, participated in the recording. They wear EEG devices on their scalps, which connect to computers running software like MuseLSL2 or Unicorn Suite. After starting the EEG data stream, the signal quality is checked in the applications. The LabRecorder and Keyboard Stroke program is launched, the setup is tested, and the recording begins by clicking the start button in LabRecorder.

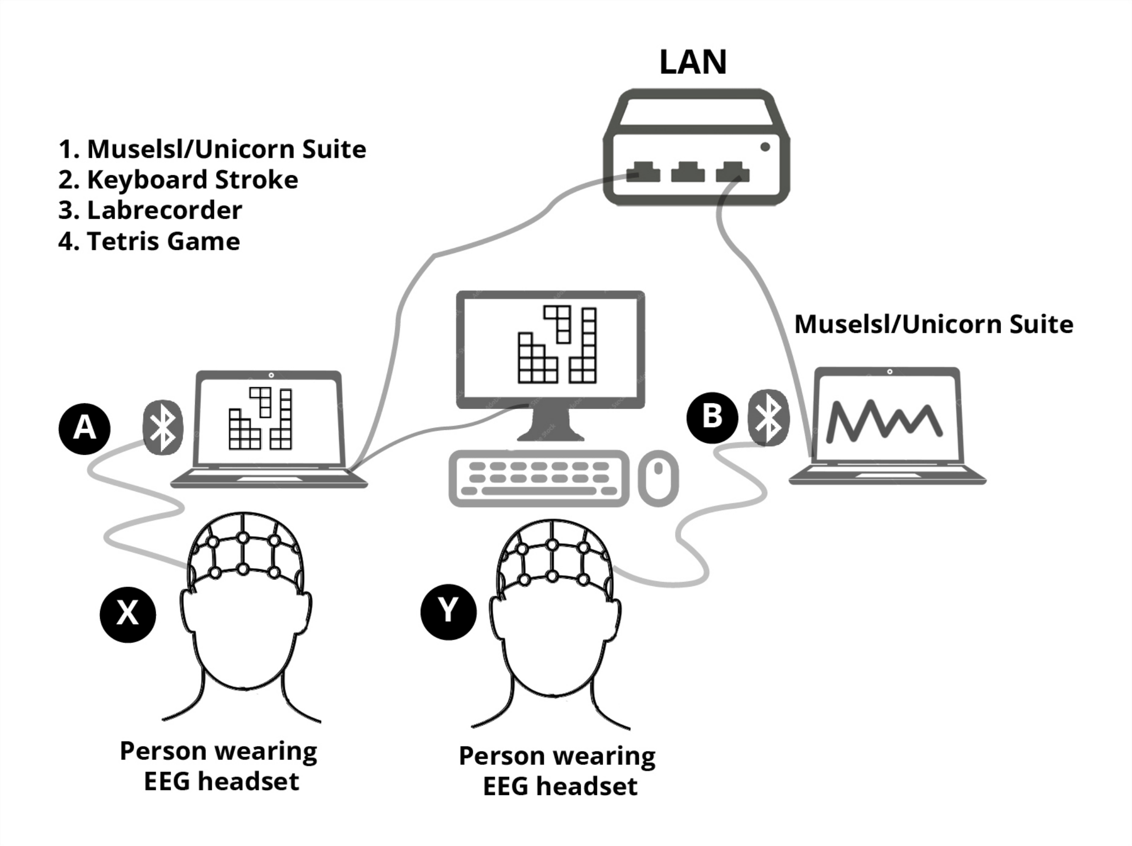


Figure 4.3 *EEG hyperscanning recording setup*

There is no fixed order to follow for EEG hyperscanning setup, as it is influenced by individual preferences. However, the steps outlined below can be followed to set up the EEG hyperscanning recording.

1. Two laptops must be connected via an Ethernet cable to create a local network. This is necessary to save concurrent data via LabRecorder application in XDF format.

2. Participants share a common display monitor and keyboard to play the Tetris game.

3. Two participants are required whose brain EEG signals will be collected. Participants must be healthy and free from any brain-related injuries or diseases.

4. Subjects wear EEG devices. In this study, either Muse S or Unicorn Hybrid Black was used.

5. Two computers or laptops with Bluetooth technology are needed. It is good practice to check the charge levels to avoid any disruptions.

6. Participants wear EEG devices. For Unicorn Hybrid Black, a helping hand is required to apply the gel according to the guidelines.

7. Open the corresponding program that connects the computer with the EEG devices. Quickly check the signals in the program.

8. Open the keyboard stroke program that records the participants' keyboard strokes.

9. Open LabRecorder and ensure that two EEG-supported devices and the keyboard program are listed. Check the corresponding devices and the keyboard program.

10. Open the Tetris game and click the start button in LabRecorder.

11. One of the participants presses the 'x' key, which will echo "Relaxation Starts." The participant then closes their eyes until the keyboard program echoes, "Relaxation Ends."

12. Participants then play Game 1, which is Common Well. After the first game, one participant pressed the 'x' key for the second relaxation period, and the process continues until three games and four relaxation complete.

EEG Recording Application

The following open-source Python scripts were used to read EEG data from the Muse S headband.

MuseLSL2

MuseLSL2 is an open-source Python script created by InteraXon that is designed to stream, visualize, and record EEG data from Muse devices. MuseLSL2 is the re-implementation of MuseLSL. MuseLSL showed two different timestamps while recording EEG data via EEG devices. MuseLSL2 fixed it by incorporating mne-lsl and other Python packages [78].
A laptop equipped with Bluetooth is essential to operate this application. It needs to be installed on a device running Python 3, along with specific Python package dependencies. A detailed installation guide is available in their code repository[78].

```
MuseLSL2 find
MuseLSL2 stream --address xx:xx:xx:xx:xx:xx -p -c -g
MuseLSL2 view
```

After connecting the Muse S headband via Bluetooth, the Muse S streams EEG data by following the command. Here, the address refers to the Mac address of the Muse S headband. The first command line can find the Muse S MAC address. The second command starts the stream, and the last opens a window showing the Muse S signals.

Unicorn suite

The Unicorn Suite, the complete software environment for Unicorn Hybrid Black, includes user-ready and programmable applications. It always comes with the Unicorn Hybrid Black. It requires license key to install in laptop. EEG signals can be checked in Unicorn suite.

Keyboard Storke

The program was developed using Python packages to track participants' keyboard strokes while playing the Tetris game in hyperscanning recordings. This Python script is developed according to LSL protocol.

4.3 Recording protocol

An easy way to synchronize data from multiple systems is by using LabRecorder. It comes with LSL is a network protocol for streaming data within a local network. The protocol manages networking and time synchronization for all data streams. LSL uses standard Internet protocols to send and receive data. It allows to synchronize streams from devices or apps connected to the same network, whether WAN or LAN. It does not require configuration and handles network delays and jitters, enabling connection recovery, offset correction, and jitter compensation. These features ensure accurate and continuous data recording, even during interruptions. It supports over 150 devices, including Muse S and Unicorn Hybrid Black [79].

LabRecorder

In this EEG hyperscanning setup, the LabRecorder application is used to capture data from two EEG devices and keyboard strokes. LabRecorder application comes up with LSL, a data streaming protocol that supports unified measurement time series. Figure 4.4 is the UI of the LabRecorder Application.

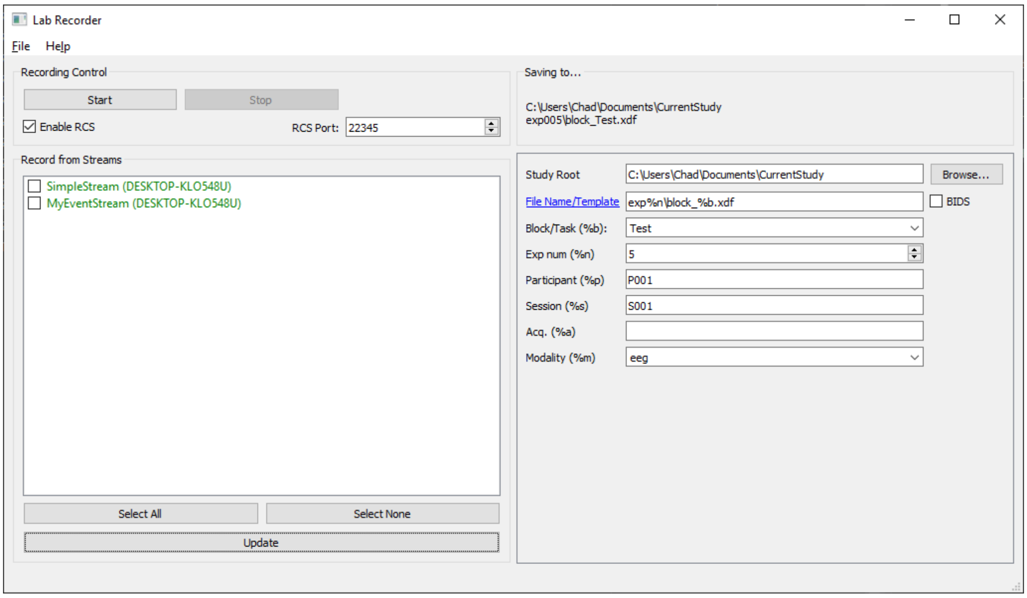


***Figure** 4.4 LabRecorder user interface source:`https://github.com/labstreaminglayer/App-LabRecorder`*

Description of Task

Tetris is a puzzle game invented by Russian computer Engineer Alexey Leonidovich Pajitnov, which was released in 1987 [80].

The version of the Tetris game is open source, and can be played by single or two players [81]. It is also available in STEAM platform [81].

Figure 4.5 illustrates the user interface of Tetris Game.

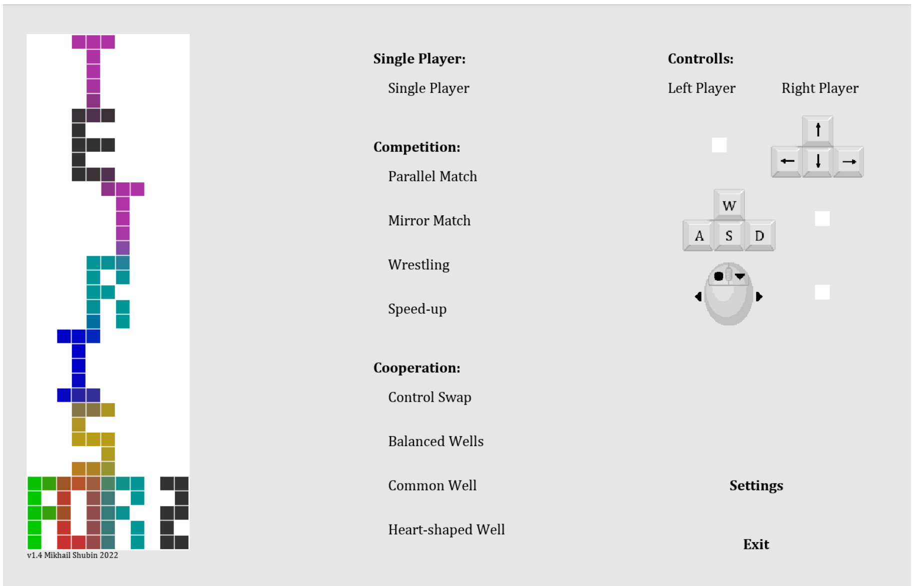
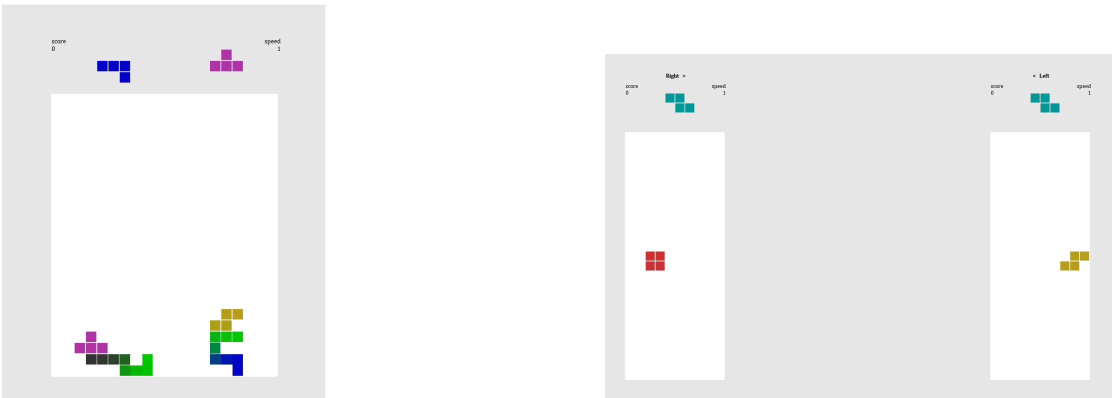


Figure 4.5 *Tetris Graphical User Interface*

In this study, the following games were played during the recordings: Common Well and Control Swap. The user interface for Common Well is shown in Figure 4.6(a), while that for Control Swap is shown in Figure 4.6(b). The interface for Parallel Match is identical to that of Control Swap.



(a) Tetris Common Well

(b) Tetris Control Swap

Figure 4.6 *User interfaces for Tetris Common Well and Control Swap.*

The Common Well task can be categorized as a collaborative activity, while the Control Swap game represents a cooperative task. Each recording session consisted of seven phases, as depicted in Figure 4.7, which illustrates the recording protocol of two participants during the recording session. Among the seven phases, four were relaxation phases. The session began with a 60-second relaxation period, followed by the first game, Tetris Common Well. This sequence was repeated, resulting in

three games and four relaxation phases.
The relaxation periods were marked using the ”x” key on the keyboard. When participants began relaxing, one participant pressed the ”x” key, triggering the program to announce, ”Relaxation Starts” After 60 seconds, it announced, ”Relaxation End,” serving as a marker for different recording phases and helping to label them as ”Game” or ”Relaxation”

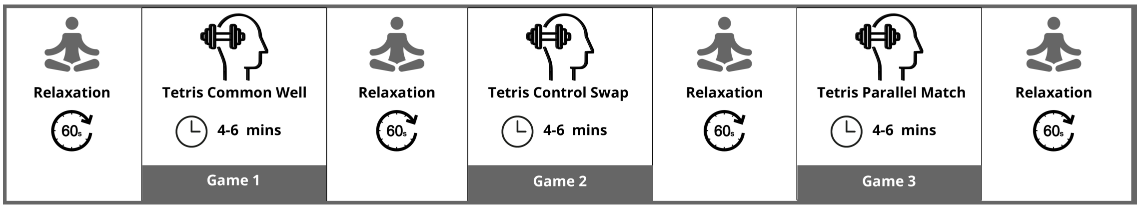


Figure 4.7 *Recording protocol*

4.4 Challenges

During hyperscanning recordings, two main problems occurred: timestamp mismatch and connection dropouts from the Muse S devices. MuseLSL2 fixed the timestamp issue, but the connection dropouts continued even after trying different hardware and software. In the following section, both issues will be discussed briefly.

Timestamp Mismatch

In the hyperscanning recording setup, MuseLSL, an open-source Python program, captured the Muse S stream. LabRecorder stored two EEG streams. However, the MuseLSL App showed mismatched timestamps for the EEG data [78]. To address this, MuseLSL2 [82], a newer version of MuseLSL, was employed. It integrated mne-lsl Python packages and eliminated pulls, resolving the timestamp mismatch. After applying this program, the timestamps were successfully synchronized.

Connection Dropout

Initially, Muse S was chosen for EEG hyperscanning recordings. Several recordings were conducted, with an average duration of approximately 1000–1200 seconds. During these recordings, one of the Muse S devices often disconnected randomly, typically after about 10 minutes. Occasionally, the Muse S connection drops out near the end of a recording.
Two Raspberry Pi 4.0 devices were initially used to set up the hyperscanning recording. After experiencing several connection dropouts, the issue was suspected to be

related to the Raspberry Pi's Bluetooth capabilities, as Raspberry Pi is designed for more straightforward tasks and lacks a powerful processor. Consequently, a pair of laptops was used instead of Raspberry Pi 4.0 computers, with the expectation that this would resolve the connection dropout issue. However, connection dropouts persisted even with the laptops.

Several open-source and paid programs, such as CleanRoom and Petal, were tested to address the issue. Additionally, a Bluetooth dongle was used instead of the laptop's built-in Bluetooth, as some forums suggested this as a potential solution. However, none of these approaches resolved the connection dropout issue.

While using the Petal app to collect EEG data, it was observed that multiple timestamp data points were not straight lines as they should have been. Instead, there were several breakpoints in the timestamp data. This observation implies that the problem originates from the Muse S devices, not the software or laptops.

CHAPTER 5

EEG Data Analysis

In this chapter, following data analysis topics will be covered briefly: data preprocessing, feature extraction, classification and compare result of Muse S and Hybrid Hybrid Black data. Figure 5.1 illustrates the steps from data preprocessing to classification.

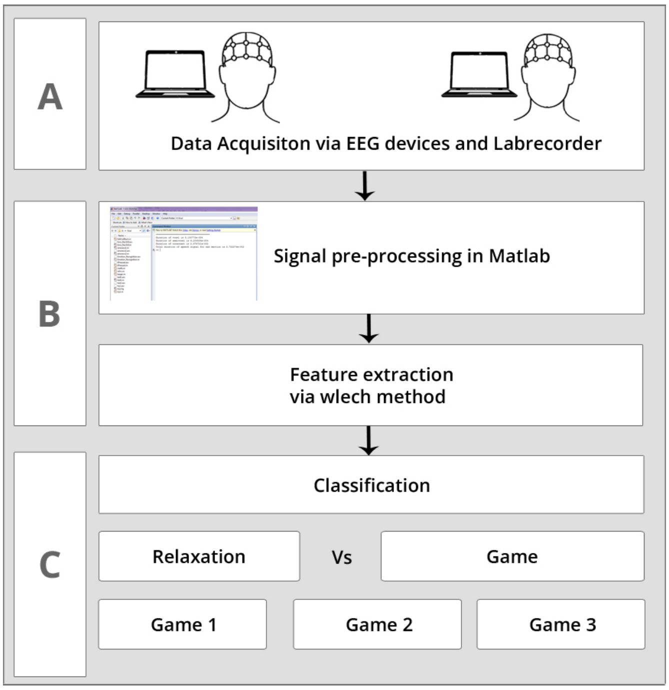


Figure 5.1 *Data preprocessing to classification*

5.1 Data Preprocessing

A total of ten pairs of subjects were selected for this study, five pair of subjects from Muse S and five from Unicorn Hybrid Black. The EEG data and keyboard stroke streams were saved in xdf format using LabRecorder, which recorded multiple streams, including time-series, markers, and meta-data, into one XDF file. Initially, the xdf files are loaded into Matlab for signal pre-processing. The Signal Processing Toolbox and the following open-source code were used to handle the xdf files [83].
In xdf files, there are three combined data saved in xdf files through Labrecorder. Two EEG stream data and one keyboard stroke data.
The code conducts the following preprocessing steps in MATLAB:

1. Filtering: The raw EEG signals were pre-processed to remove artifacts. A 6th-order Butterworth bandpass filter was applied with a frequency range of 0.5–40 Hz to remove irrelevant frequencies noise signals.

2. Resampling: The EEG data is resampled to a standard sampling rate of 256 Hz for the Muse S and 250 Hz for the Unicorn Hybrid Black. The resample function adjusts the sampling rate of EEG data streams across all channels, ensuring that both datasets are aligned temporally and sampled at the same frequency. This step is essential for hyperscanning analysis.

3. Segmentation: The relaxation and game phases are identified by marking the data according to keyboard strokes 'x'. Afterward, the EEG data is split into 10-second windows with a 20% overlap for further examination.

5.2 Feature Extraction

The following features are extracted to analyze the EEG signals:

1. **Spectral Analysis**:

   Spectral analysis involves calculating the Power Spectral Density (PSD) for each EEG segment using the Welch method, followed by normalization by dividing the PSD by its maximum power value to ensure consistent scaling.

2. **Coherence Analysis**:

   Coherence analysis uses magnitude-squared coherence (MSC) to measure synchronization between EEG channels, both within a single device (intra-brain coherence) and between devices (inter-brain coherence), with the Muse S EEG headband utilizing only the frontal channels (AF7, AF8) for these calculations.

Feature Matrix

- **Muse S Feature Matrix:**
  - 91 frequency bins (from 0 to 45 Hz at 0.5 Hz intervals).
  - The feature matrix for each segment is a 3D array of shape $91 \times \text{number\_of\_segments} \times 10$, where:
    - 10 features include:
      - PSD for 4 channels (2 from each device).
      - Intra-brain coherence for each device (2 values).
      - Inter-brain coherence across channels (4 values).

Table 5.1 illustrates the combination of power spectral density and coherence.

Number	Channel / Coherence	
Individual Channels		
1.	Stream 1: AF7	
2.	Stream 1: AF8	
3.	Stream 2: AF7	
4.	Stream 2: AF8	
Intra-coherence		
5.	Stream 1 AF7	Stream 1 AF8
6.	Stream 2 AF7	Stream 2 AF8
Inter-coherence		
7.	Stream 1 AF7	Stream 2 AF7
8.	Stream 1 AF7	Stream 2 AF8

Table 5.1 *Combinations of power spectral density and coherence*

- **Unicorn EEG Feature Matrix:**
  - Two types of classification are performed: one using all possible features, totaling 136, and another using only cross-coherence, which involves 64 features.
  - The feature matrix for each segment is a 3D array of shape $91 \times \text{number\_of\_segments} \times 136$ or $91 \times \text{number\_of\_segments} \times 64$.

5.3 Classification

Two EEG devices were used in the study: Muse S and Unicorn Hybrid Black. The dataset was divided into three categories based on the number of features: 10 features for Muse S headband, 136 and 64 features set for Unicorn Hybrid Black EEG headset.

By combining the feature sets, classification categories, and cross-validation methods, a total of 12 types of analysis were performed. Table 5.2 illustrates the combination of classification type with cross-validation method.

Table 5.2 *Summary of feature Set, classification, and cross-validation Methods*

Random Cross Validation		
No	**Feature Set**	**Binary Classification**
1	Muse S	Relaxation vs Game
2	Unicorn All Feature Set	Relaxation vs Game
3	Unicorn Cross Coherence	Relaxation vs Game
Leave-One-Subject-Out Cross Validation		
4	Muse S	Relaxation vs Game
5	Unicorn All Feature Set	Relaxation vs Game
6	Unicorn Cross Coherence	Relaxation vs Game
Random Cross Validation		
No	**Feature Set**	**Multi-class Classification**
7	Muse S	Game 1 vs Game 2 vs Game 3
8	Unicorn All Feature Set	Game 1 vs Game 2 vs Game 3
9	Unicorn Cross Coherence	Game 1 vs Game 2 vs Game 3
Leave-One-Subject-Out Cross Validation		
10	Muse S	Game 1 vs Game 2 vs Game 3
11	Unicorn All Feature Set	Game 1 vs Game 2 vs Game 3
12	Unicorn Cross Coherence	Game 1 vs Game 2 vs Game 3

Cross-Validation Methods

To evaluate the performance of these classifications, two cross-validation methods were employed:

1. Random Cross-Validation (Random CV): Each feature set was randomly split into training and testing data for 50 iterations.

2. Leave-One-Subject-Out Cross-Validation (LOSO CV): In this method, one subject's data was excluded for testing while the rest dataset was used for training. This process was repeated for every subject.

Random Cross Validation

A random cross-validation method was performed for the binary and multi-class classifications. In the binary classification task, the goal is to separate between relaxation and game. The multi-class classification task aims to classify data into three categories: Game1, Game2, and Game3.
In random cross-validation, the training and testing processes are repeated for fifty iterations, resulting in robust and reliable evaluation metrics for binary and multi-class classification.

1. Loading and Preprocessing Data:
   - Two separate datasets were used for classification tasks: Relaxation vs Game: Feature matrix were converted into images to use in CNN classification.
   - Each image is resized to a fixed size and converted to grayscale for uniformity. The images are normalized to have pixel values between 0 and 1, making them suitable for neural network input.
2. Data Splitting Using ShuffleSplit:
   - For both classification tasks, the dataset is split into training and testing sets using `ShuffleSplit`.
   - The data is shuffled, and each split holds 20% for testing and 80% for training. This split process is repeated for fifty(50) iterations. Iteration helps to evaluate the model performance.
3. Model Creation:
   - A Convolutional Neural Network (CNN) is created for feature extraction and classification.
   - The architecture includes:
     – Convolutional Layers: These layers apply filters to the input images to extract spatial features.
     – Max-Pooling Layers: These layers reduce the spatial dimensions (width and height) of the feature maps, making the network more computationally efficient and preventing overfitting.
     – Dropout Layers: These layers randomly drop units during training to prevent overfitting.

  - Fully Connected Layers: These layers perform the final classification after feature extraction.

- The final output layer's activation function is selected based on the classification type: `sigmoid` for binary classification (Relaxation vs Game) and `softmax` for multi-class classification (Game 1 vs Game 2 vs Game 3).

4. Model Training:

   - The CNN model is trained using the training dataset, where images are reshaped and normalized.
   - `Adam` optimizer is used with a learning rate, and the model is trained over 120 epochs with a batch size of 200.
   - `binary_crossentropy` loss function is used for binary classification, while `categorical_crossentropy` is used for multi-class classification.
   - Training includes a validation split to monitor overfitting and ensure the model generalizes well.

5. Model Evaluation:

   - After training, the model is evaluated on the test set. Performance metrics include Accuracy, sensitivity, specificity, and confusion matrix for each split. Sensitivity and specificity are calculated from the confusion matrix. It is used to assess the classification performance by showing the true and predicted class labels.

Leave-One-Subject-Out Cross-Validation (LOSO CV)

In this study, there were five datasets for each model. In each model, the subject was defined for training and testing purposes. In each case, four datasets were used for training, and one was left out or excluded for testing purposes to evaluate the model and how it performed in totally unknown data. Here are the essential steps for a LOSO CV.

- **Define the Subjects:** Identify the subjects (or participants) in the dataset, ensuring each subject is represented in a unique fold during cross-validation.
- **Split the Data:** For each fold, use all but one subject for training and the left-out subject for testing.

- **Maintain Consistency Across Tasks:** Ensure that the same subject is consistently assigned to the same fold across binary and multi-class classification tasks.

5.4 Results

This section will compare and analyze the results of the Muse S and Unicorn Hybrid Black features set. The first part will discuss the Muse S feature and Unicorn Hybrid Black datasets.

Results obtained from Muse S

Table 5.3 shows the results of Muse S random and LOSO cross-validation for classifying Relaxation versus Game

Muse: Relaxation vs Game		
Metric	Random Cross Validation	LOSO
Accuracy (±Std)	0.9398 ± 0.0122	0.7100 ± 0.0889
Sensitivity (±Std)	0.9538 ± 0.0174	0.7480 ± 0.1219
Specificity (±Std)	0.8838 ± 0.0364	0.5740 ± 0.3224

Table 5.3 *Random and LOSO Cross Validation for binary classification (Relaxation vs Game)*

Table 5.4 compares the Muse S dataset's LOSO CV results across two tasks: Relaxation vs. Game (Binary) and Game 1 vs. Game 2 vs. Game 3 (Multi-class validation).

Muse: Game1 vs Game2 vs Game3		
Metric	Random Cross Validation	LOSO
Accuracy (±Std)	0.8192 ± 0.0297	0.4480 ± 0.0817
Sensitivity (±Std)	0.8267 ± 0.0954	0.4453 ± 0.3044
Specificity (±Std)	0.9114 ± 0.0381	0.7233 ± 0.2672

Table 5.4 *Random and LOSO Cross Validation for Muse: Game1 vs Game2 vs Game3 classification*

Result overview of Muse S

Relaxation and game types were easily separated with random cross-validation. However, with LOSO (Leave-One-Subject-Out) cross-validation, the classification accuracy for Muse S fall down due to the lack of subjects for this technique.

Results obtained from Unicorn data set

In Table 5.5, the Unicorn Hybrid Black dataset's random cross-validation is compared across two tasks: Relaxation vs. Game (Binary) and Game 1 vs. Game 2 vs. Game 3 (Multi-class validation).

Unicorn: Relaxation vs Game		
Metric	Random Cross Validation	LOSO
Accuracy (±Std)	0.9960 ± 0.0049	0.9040 ± 0.0777
Sensitivity (±Std)	0.9966 ± 0.0048	1.0000 ± 0.0000
Specificity (±Std)	0.9988 ± 0.0039	0.4740 ± 0.3900

Table 5.5 *Random and LOSO Cross Validation for Unicorn: Relaxation vs Game classification*

In Table **??**, the Unicorn Hybrid Black dataset's random cross-validation is compared across two tasks: Relaxation vs. Game (Binary) and Game 1 vs. Game 2 vs. Game 3 (Multi-class validation).

Unicorn: Game1 vs Game2 vs Game3		
Metric	Random Cross Validation	LOSO
Accuracy (±Std)	0.8512 ± 0.0115	0.3420 ± 0.0572
Sensitivity (±Std)	0.8511 ± 0.0542	0.3607 ± 0.3132
Specificity (±Std)	0.9250 ± 0.0338	0.6793 ± 0.2858

Table 5.6 *Random and LOSO Cross Validation for Unicorn: Game1 vs Game2 vs Game3 classification*

Result overview of Unicorn full feature set

Overall, For Random cross-validation and LOSO, Binary classification for the Unicorn full feature performed better than multi-class classification in all matrics sensitivity, specificity, and Accuracy, and the score is approximately 99%. In contrast, multi-class classification ranges from 85% to 92%.
For LOSO CV, binary classification shows similar to random cross-validation. However, it could have performed better for multi-class classification. It ranges from 33% to 66%

Unicorn Cross Coherence

Table 5.7 compares the Unicorn Hybrid Black dataset's LOSO CV results across two tasks: Relaxation vs. Game (Binary) and Game 1 vs. Game 2 vs. Game 3 (Multi-class validation).

Unicorn: Cross Coherence: Relaxation vs Game		
Metric	Random Cross Validation	LOSO
Accuracy (±Std)	0.9910 ± 0.0042	0.9850 ± 0.0100
Sensitivity (±Std)	0.9924 ± 0.0043	0.9900 ± 0.0000
Specificity (±Std)	0.9914 ± 0.0140	0.9425 ± 0.0690

Table 5.7 *Random and LOSO Cross Validation for Unicorn: Cross Coherence: Relaxation vs Game classification*

Table 5.8 compares the Unicorn Hybrid Black dataset's LOSO CV results across two tasks: Relaxation vs. Game (Binary) and Game1 vs. Game2 vs. Game3 (Multi-class classification).

Unicorn: Cross Coherence: Game1 vs Game2 vs Game3		
Metric	Random Cross Validation	LOSO
Accuracy(± Std)	0.3668 ± 0.0163	0.3120 ± 0.0311
Sensitivity(± Std)	0.3327 ± 0.4703	0.3327 ± 0.4841
Specificity(± Std)	0.6668 ± 0.4718	0.6667 ± 0.4865

Table 5.8 *Random and LOSO Cross Validation for Unicorn: Cross Coherence: Game1 vs Game2 vs Game3 classification*

Result overview of Unicorn cross coherence feature set

Overall, for both cross-validation methods, Relaxation vs Game (binary classification) performs better than Game1 vs Game2 vs Game3 (multi-class classification) regarding sensitivity, Accuracy, and overall performance. However, specificity is higher for the multi-class classification task in Random Cross-Validation and LOSO Cross-Validation.

CHAPTER 6

Conclusion

In this chapter, the results will be used to conclude the study, offering a comprehensive summary of the findings.
In binary classification, relaxation and game performed better for random cross-validation. For LOSO(Leave-One-Subject-Out) cross-validation, classification accuracy dropped for Muse S due to lack of subjects. In LOSO(Leave-One-Subject-Out) cross-validation, the model trained on four subjects and tested on one subject became overfitted and could not be generalized.
Unicorn data's accuracy was impressive for ransom cross-validation and LOSO cross-validation, even when only interbrain coherence features were used. Interestingly, for binary classification, the Unicorn cross-coherence features provide consistent results across both Random and LOSO Cross-Validation in all metrics. It requires further verification.
In multi-class classification for three game types, accuracy dropped. With random cross-validation, the accuracy remained relatively high, likely because the model learned to recognize subjects (as data from all subjects was used for training and testing). However, results for LOSO were worse, almost approaching random guessing. When only interbrain features were utilized for Unicorn data, relaxation and game were still easily distinguished, showing that interbrain coherence data still carries some information to separate these two classes. However, classifying the three game types resulted in accuracy close to random.

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